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(54) **ASSOCIATING AN ENTITY WITH A CATEGORY**

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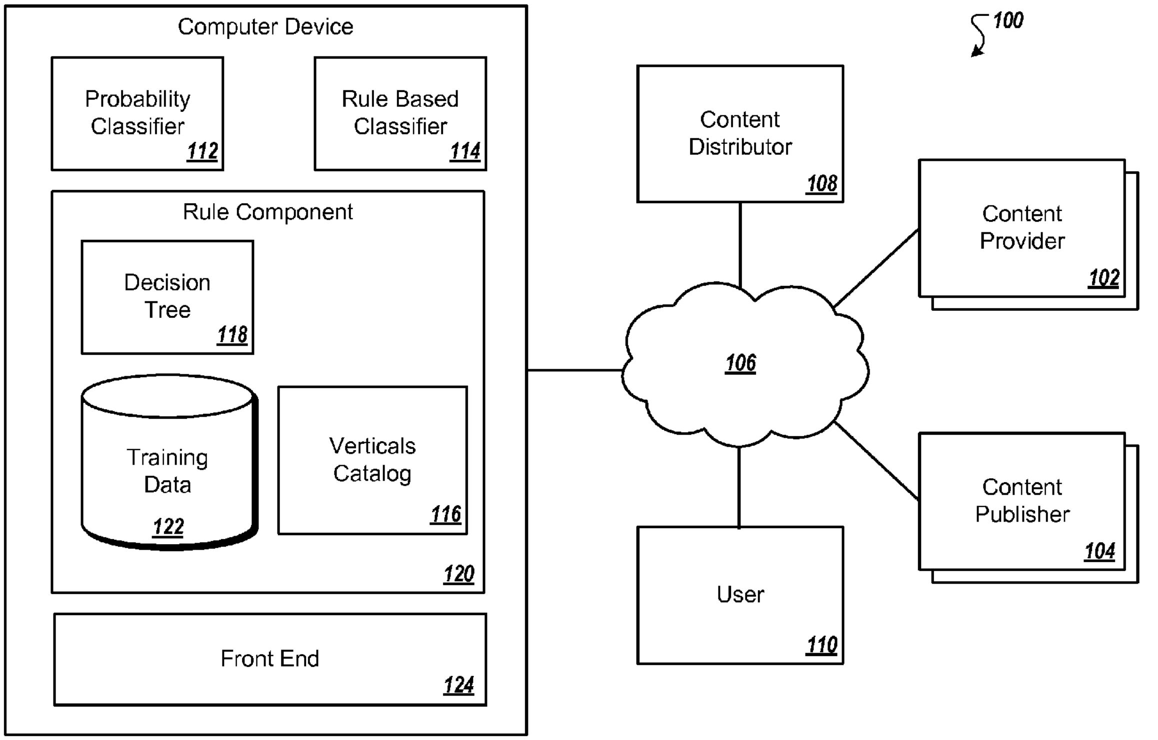
(57) **ABSTRACT**

Among other disclosed subject matter, a computer-implemented method for associating an entity with a category includes determining a probability value for each of at least a subset of a plurality of categories, the probability value representing a likelihood that an identified entity belongs to the respective category and determined using information about the entity. The method includes identifying one of the plurality of categories for the entity using the probability value and a rule set for the plurality of categories that is based on training data.



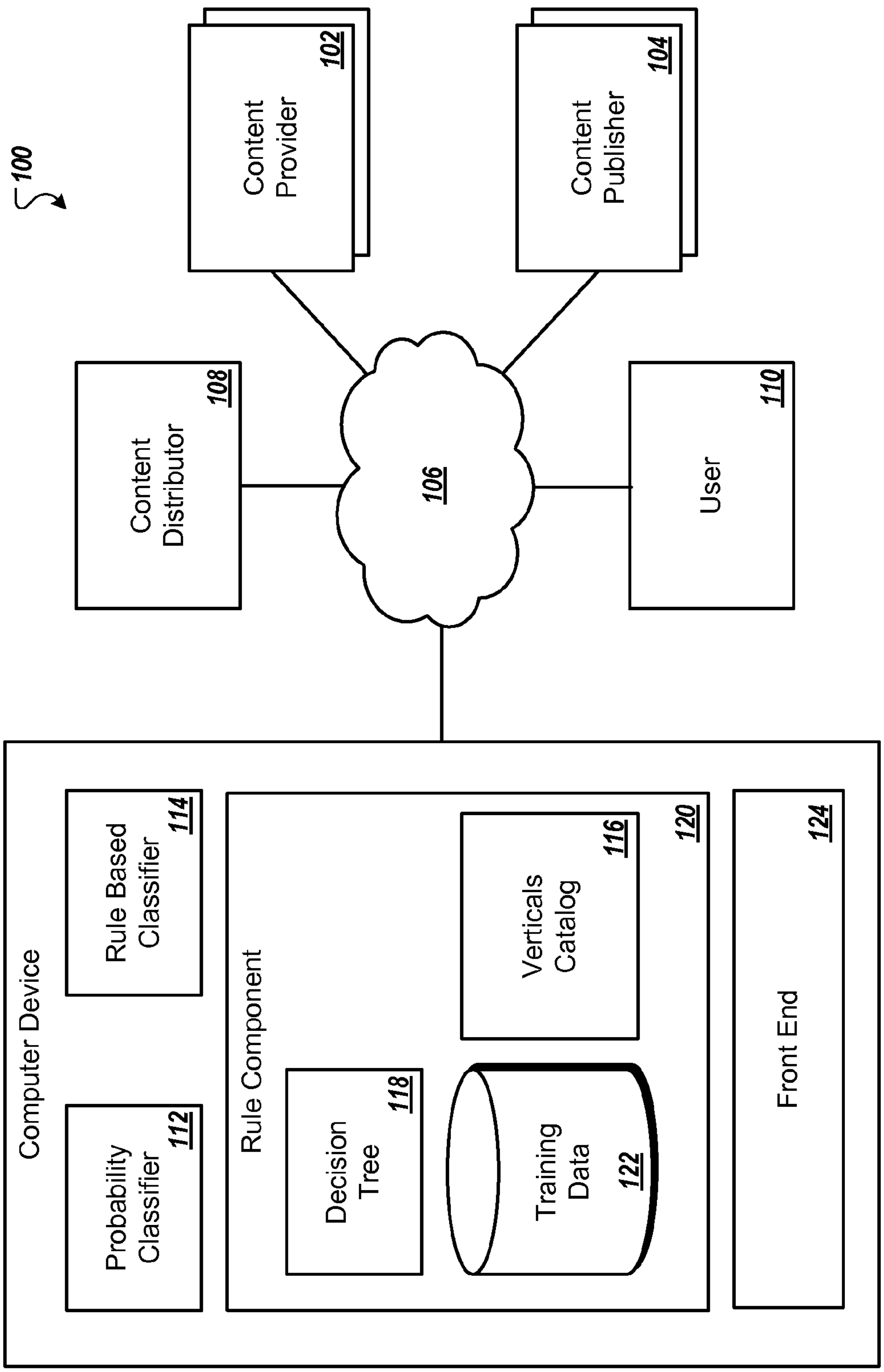

100
Content Provider
102
Content Publisher
104
Content Distributor
108
106
User
110
Computer Device
Probability Classifier
112
Rule Based Classifier
114
Rule Component
Decision Tree
118
Training Data
122
Verticals Catalog
116
120
Front End
124

FIG. 1

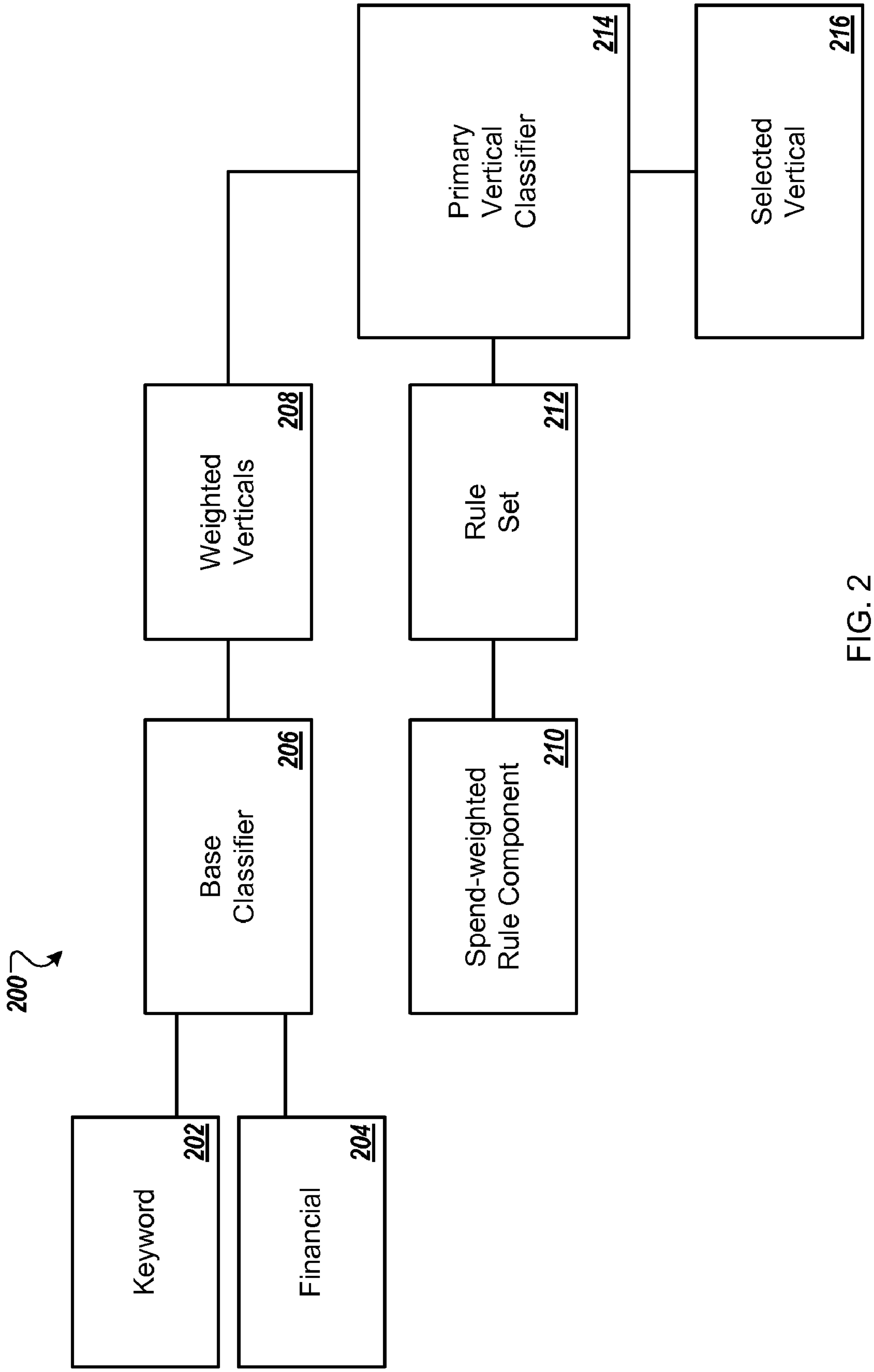

200
Keyword
202
Financial
204
Base Classifier
206
Weighted Verticals
208
Spend-weighted Rule Component
210
Rule Set
212
Primary Vertical Classifier
214
Selected Vertical
216

FIG. 2

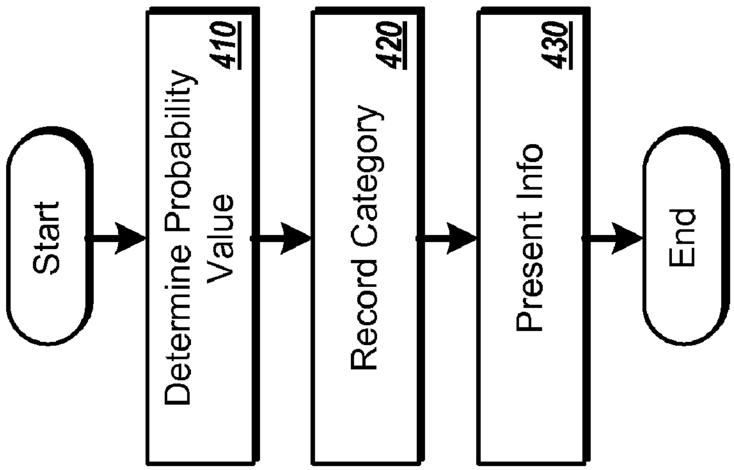

Start
Determine Probability Value
410
Record Category
420
Present Info
430
End

FIG. 4

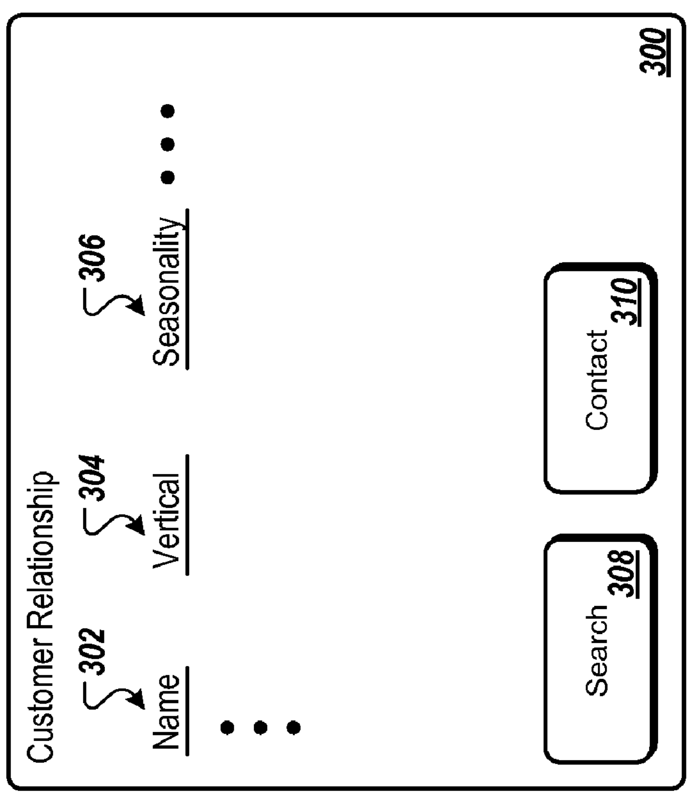

Customer Relationship
302
Name
304
Vertical
306
Seasonality
Search
308
Contact
310
300

FIG. 3

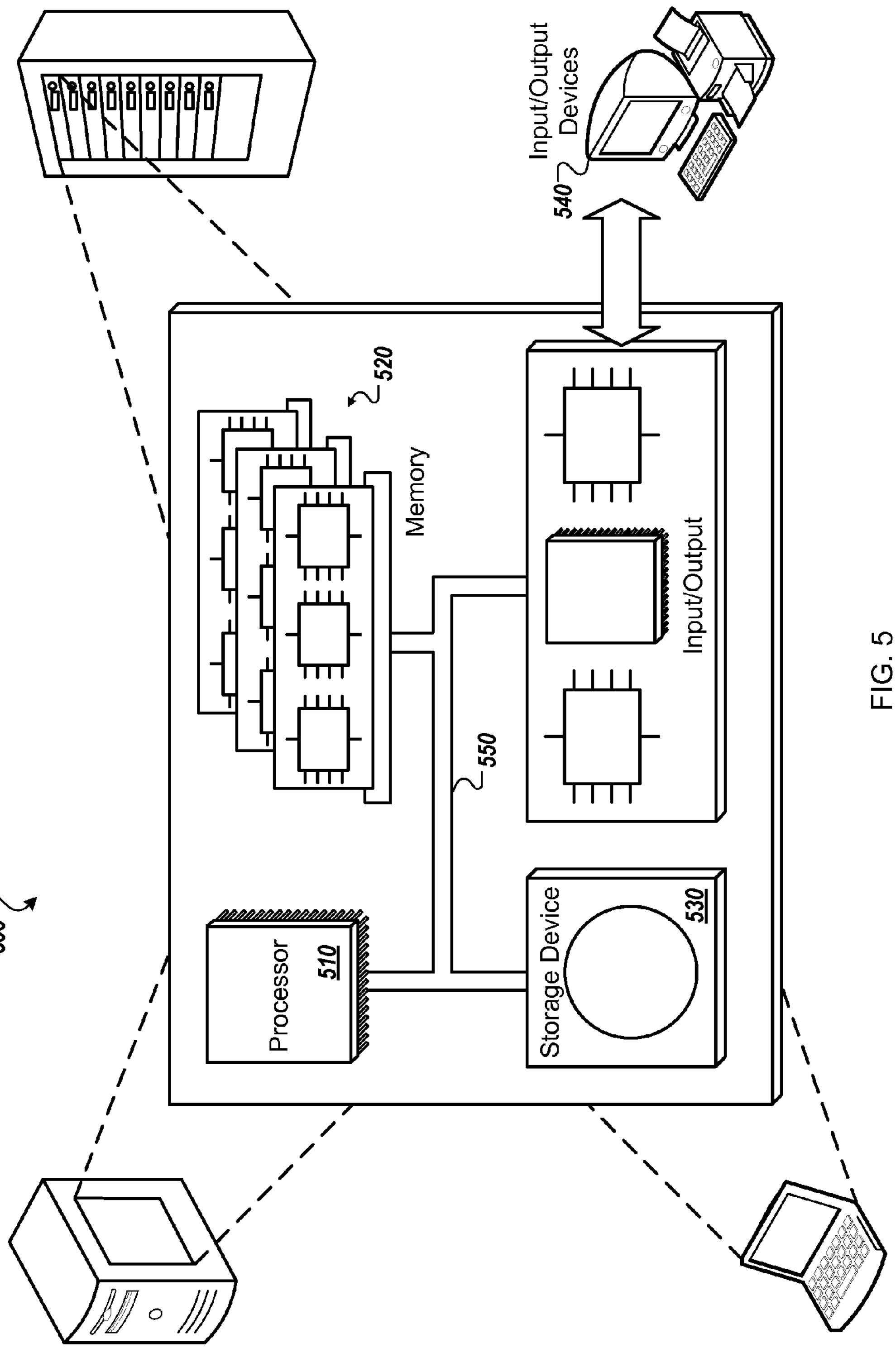

500
Processor
510
Storage Device
530
Memory
520
Input/Output
550
Input/Output Devices
540

FIG. 5

ASSOCIATING AN ENTITY WITH A CATEGORY

RELATED APPLICATIONS

[0001] This application claims priority under 35 USC §119 (e) to U.S. Provisional Patent Application Ser. No. 61/097,026, filed on Sep. 15, 2008, the entire contents of which are hereby incorporated by reference.

TECHNICAL FIELD

[0002] This document relates to information processing.

BACKGROUND

[0003] Advertisers can run advertisement campaigns in any of multiple different platforms, including the Internet, television, radio, and billboards. Advertisements used in advertising campaigns can cover a range of products and services and can be directed toward specific audiences or more generally toward the greater population. For example, publishers operating websites can provide space to advertisers for presenting advertisements. Advertisements presented on a website are sometimes selected based on the content of the website.

SUMMARY

[0004] The invention relates to associating an entity with a category.

[0005] In a first aspect, a computer-implemented method for associating an entity with a category includes determining a probability value for each of at least a subset of a plurality of categories, the probability value representing a likelihood that an identified entity belongs to the respective category and determined using information about the entity. The method includes recording one of the plurality of categories for the entity, the category identified using the probability value and a rule set for the plurality of categories.

[0006] Implementations can include any, all or none of the following features. The entity can be a content provider identified as enrolled in a program in which the content provider provides content to be published by at least one publisher, and the probability value can be determined using at least one keyword associated with the content provider and at least one financial value associated with the content provider. Determining the probability value can include mapping the at least one keyword at least to the subset of the plurality of categories; weighting at least the subset with the at least one financial value, wherein the financial value has been assigned to the corresponding keyword; and selecting a predetermined number of the categories as the subset. The rule set can be based on training data. The rule set can include a decision tree configured for selecting one of the plurality of categories by processing at least some of a plurality of decisions included in the decision tree. The method can further include generating the decision tree using the training data, wherein the training data comprises mappings of entities to one or more of the plurality of categories. Generating the decision tree can further include weighting the mappings using financial data regarding the entities. Weighting the mappings can further include oversampling at least a subset of the mappings based on the financial data corresponding to the subset of the mappings. Generating the decision tree can include selecting a structure for the decision tree; determining an extent of the decision tree, including how many of the plurality of decisions to be made before the one of the plurality of categories is selected; and determining threshold values to be used in the plurality of decisions. The decision tree can be generated iteratively. The content provider can be engaged in advertising and the plurality of categories can include verticals with which the content provider is to be matched. Generating the decision tree can further include identifying at least one of the verticals for which the determination of the probability values has a tendency to improperly assign the vertical to the content provider; and selecting at least one of the threshold values so that the tendency is reduced. The method can further include presenting information to a user based on the category having been identified for the entity. The information can indicate a seasonality associated with the category.

[0007] In a second aspect, a computer system includes a first classifier determining a probability value for each category of at least a subset of a plurality of categories, the probability value representing a likelihood that an identified entity belongs to the respective category and determined using information about the entity. The system includes a second classifier identifying one of the plurality of categories for the entity using the probability value and a rule set for the plurality of categories.

[0008] Implementations can include any, all or none of the following features. The rule set can be based on training data. The first classifier can take into account a financial value relating to the entity in determining the probability value. The rule set can include a decision tree configured for selecting one of the plurality of categories by processing at least some of a plurality of decisions included in the decision tree, and the computer system can further include a rule component generating the decision tree using the training data, wherein the training data comprises mappings of entities to one or more of the plurality of categories. The rule component can weight the mappings using financial data regarding the entities, including oversampling at least a subset of the mappings based on the financial data corresponding to the subset of the mappings. The system can further include a front end component presenting information to a user based on the second classifier having identified the category for the entity.

[0009] In a third aspect, a computer-implemented method for associating a content provider with a category includes identifying a content provider as enrolled in a program in which the content provider provides content to be published by at least one publisher. The method further includes receiving at least one keyword regarding the content provider and at least one financial value regarding the keyword. The method further includes receiving a plurality of categories, wherein the content provider is to be associated with at least one of the categories. The method further includes mapping the at least one keyword to a subset of the categories based on names of the categories. The method further includes associating each of at least the subset of the categories with a probability value representing a likelihood that the content provider should be associated with the respective category, the probability values weighted using the financial value. The method further includes receiving a rule set generated regarding the plurality of categories, the rule set configured for use in identifying one of the categories. The method further includes processing data regarding the content provider using the rule set, the data including at least: (i) the probability value for each of at least the subset of the categories (ii) financial data regarding the content provider; (iii) a geographic region with which the content provider is associated. The method further includes selecting one of the plurality of categories for the content

provider based on the processing of the data. The method further includes associating the content provider with the selected category.

[0010] Implementations can provide any, all or none of the following advantages. Improved classification into categories can be provided. A probability-based classification can be revenue-weighted and can be made further specific by a rule-based classification previously trained using training data. Flexibility in classification can be increased.

[0011] The details of one or more embodiments are set forth in the accompanying drawings and the description below. Other features and advantages will be apparent from the description and drawings, and from the claims.

DESCRIPTION OF DRAWINGS

[0012] FIG. **1** shows an example system that can identify a category for an entity.

[0013] FIG. **2** shows another example system that can identify a category for an entity.

[0014] FIG. **3** shows an example user interface that can present information based on a category having been identified for an entity.

[0015] FIG. **4** shows an example method that can be performed to identify a category for an entity.

[0016] FIG. **5** is a block diagram of a computing system that can be used in connection with computer-implemented methods described in this document.

[0017] Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

[0018] FIG. **1** shows an example system **100** that can identify a category for an entity. Multiple entities can operate in the system **100**, for example, entities can be of the form of content providers such as advertisers and content publishers such as owners of web pages or other contents. In some implementations, the content providers can operate one or more content provider systems **102** and the content publishers can operate one or more content publisher systems **104**. Any kind of computer device, electronic device or system can be included in the systems **102** and **104**, such as a server computer or a personal computer. Components in the system **100** can communicate with each other using any kind of network **106**, such as a local computer network or the Internet.

[0019] In some implementations, one or more entities in the system **100** can be involved in a transaction in which a content provider provides content to be published by at least one publisher. For example, content such as an advertisement can be distributed from the content provider system **102** over the network **106** for publication on behalf of one or more of the content publisher systems **104**. In some implementations, the content can temporarily or permanently be held by a third party, such as a content distributor system **108** (e.g., an advertisement server) and can be distributed from the system **108** for publication. For example, when a user system **110** requests media content (e.g., a web page) from the publisher system **104**, the content distributor system **108** can provide associated content (e.g., an advertisement) to the user system **110** for presentation in connection with the requested content. Below will be described examples in which one or more entities, such as a content provider and/or a content publisher in the system **100**, can be classified using a catalog of categories. Such classification can be useful to anyone involved with the classified entity, for example a person who manages distribution of content between entities.

[0020] The system **100** can include one or more classifiers. In some implementations, the system **100** includes a probability classifier **112** and a rule based classifier **114**. Names for these and other components are here used broadly, rather than narrowly; for example, the probability classifier **112** can use one or more rules in its operation, and the rule based classifier **114** can determine or use one or more probabilities in the classification process. The classifiers **112** and **114** can be implemented in any form, such as using software, hardware, firmware, or combinations thereof.

[0021] In some implementations, the classifiers **112** and **114** can be used in an effort to match a selected entity, such as the content provider operating the system **102**, with one or more categories, such as verticals from a verticals catalog **116**. A vertical can refer to one or more business classifications, such as the categorization terms sometimes used in marketing analysis to represent businesses and customers that trade in a common field (e.g., a consumer electronics vertical, or a cosmetics vertical). Other classifications can be used.

[0022] The probability classifier **112** can determine, for an entity such as a content provider, a probability value for at least one of the verticals in the catalog **116**. The probability can represent a likelihood that the content provider belongs to the corresponding vertical. For example, the probability classifier can determine a probability that an entity "Example Company, Inc." should be classified as belonging to a "mortgage" vertical. The probability can be determined using information about the entity. In some implementations, the probability classifier **112** can determine multiple probability values, such as a value corresponding to each of at least a subset of the verticals in the catalog **116**.

[0023] The rule based classifier **114** can identify a category, such as one of the verticals in the catalog **116**, for the entity. In some implementations, the rule based classifier **114** can use one or more probabilities determined by the probability classifier **112** and a rule set such as a decision tree **118**. For example, the decision tree **118** can include a plurality of decisions and can be configured for selecting one of the plurality of verticals in the catalog **116** by processing at least some of the decisions. In some implementations, the system **100** can include a rule component **120** that generates the decision tree **118** or other rules based on training data **122**. In some implementations, the training data **122** can include mappings of entities to respective ones of the categories, such as the verticals in the catalog **116**.

[0024] A rule set such as the decision tree **118** can be generated in any of multiple ways. In some implementations, a model of the tree can be defined and the tree can then be generated based on the training data **122**. For example, a structure of the tree can be selected, such as to define that the tree should include multiple levels of binary decisions. As another example, an extent of the tree can be defined (e.g., when should the decision tree end), such as how many of the plurality of decisions are to be made before the one of the plurality of categories is selected. In some implementations, one or more decisions in the tree **118** can use a threshold value. For example, a probability (e.g., one determined by the probability classifier **112**) can be compared against the threshold value. One or more aspects of the decision tree **118** can be generated using any kind of iterative process. For example, a structure of the tree **118** can be chosen in an initial iteration and tested against representative data, such as the

training data **122**, and results of such testing can be used to generate another structure of the tree **118** in another iteration. As another example, a first set of threshold values can be determined in an initial iteration, and at least one of the values can be refined through a feedback process in one or more additional iterations.

[0025] The rule based classifier **114** can serve one or more purposes in the system **100**. In some implementations, the probability classifier **112** can have a tendency to mis-classify entities in one or more regards. For example, the classifier **114** might frequently choose an "entertainment" vertical for entities that are in fact not involved, or involved only to a small degree, in the entertainment industry. Such characteristics in the probability determination can be artifacts of how the probability classifier **112** is configured and can depend on a number of factors, which can make it difficult or impractical to resolve the problem. In some implementations, the rule based classifier **114** can be used in combination with the probability classifier **112**. For example, at least one of the threshold values in the rule set (e.g., the decision tree **118**) used by the rule based classifier **114** can be selected so as to reduce or eliminate the tendency with regard to the category at issue.

[0026] At least one category (e.g., one of the verticals in the catalog **116**) can be selected for a given entity, such as for the content provider operating the system **102**. Such a selection can be used for one or more purposes, such as to output relevant information to a user. In some implementations, the system **100** can include a front end component **124** that can use one or more category selections. For example, the front end component **124** can present information relating to the selected category or categories as a way of characterizing the entity.

[0027] FIG. **2** shows another example system **200** that can identify a category for an entity. In the system **200**, one or more information portions about an entity, such as keyword (s) **202** associated with a content provider, can be identified. In some implementations, the content provider can self-identify the keyword(s) as part of participating in a content distribution program. For example, an advertiser can register a bid on one or more keywords with the content distributor system **108** (FIG. **1**) such that the advertiser's ad can be considered for publication in contexts that relate to the keyword(s). Financial information **204** about the entity can be identified. For example, this can include revenue data, such as information about how much an advertiser spends on a particular keyword.

[0028] The system **200** can include a base classifier **206**. In some implementations, the base classifier can be configured to classify an entity, such as a content provider or a content distribution campaign, using a set of categories, such as the verticals catalog **116** (FIG. **1**). In some implementations, the base classifier **206** can map the keywords **202** to some or all of the verticals and select a predetermined number of verticals. For example, three of the verticals can be chosen as being the most representative of the entity, such as by selecting those that have the largest weights.

[0029] The base classifier **206** can map multiple keywords for a particular entity to respective verticals. The respective verticals chosen for the keywords can be merged (e.g., their respective probabilities can be averaged) to form a single categorization for the entity. In some implementations, the verticals chosen for the entity can be weighted based on the financial data **204**, such as based on the amounts spent on individual keywords. For example, verticals for keywords that account for a relatively large fraction of the content provider's or distribution campaign's spending can be given a relatively larger weight in computing the classification. In some implementations, the base classifier **206** can include the probability classifier **112** (FIG. **1**). In some implementations, an output of the base classifier **206** can include one or more weighted verticals **208**, such as at least one classifier term (e.g., the name of the vertical) associated with a weight (e.g., a number between zero and one).

[0030] The system **200** can include a spend-weighted rule component **210**. In some implementations, the component **210** can provide a policy for defining a primary one among several categories, such as among three revenue weighted verticals. For example, the component **210** can run as an offline program with regard to other components in the system **200**, such as in form of a program in the MATLAB environment developed by The Mathworks company.

[0031] The spend-weighted rule component **210** can be configured for a multi-class classification on a multidimensional feature space. In some implementations, n dimensions of features can be used for mapping to any of m dimensions. For example, the verticals catalog **116** can include 30 verticals. As another example, additional features can be identified including, but not limited to, quarterly spend of the entity, total spend of the entity, number of keywords for the entity, and billing country of the entity. Thus, a 34-dimentional feature space (i.e, n=34) can be used for a classification into any of 30 dimensions (i.e, m=30). In some implementations, one or more of the feature dimensions, such as the entity country, can be categorical. For example, a predetermined number of top countries (e.g., nine countries) can be assigned one class each, and remaining countries can be grouped in a common class. In some implementations, one or more of the feature dimensions can be a discrete or a continuous variable. For example, a key word count can be a discrete variable and/or total spend can be a continuous variable.

[0032] In some implementations, the spend-weighted rule component **210** can include the rule based classifier (FIG. **1**). For example, the component **210** can use some or all of the training data **122** to define an appropriate policy. In some implementations, the spend-weighted rule component **210** can be triggered when a new or modified set of training data becomes available, such as when human classifiers have mapped one or more entities to the verticals catalog **116**.

[0033] The spend-weighted rule component **210** can output a rule set **212** that can be used in selecting the category for the entity. In some implementations, the rule set can include a decision tree. For example, the component **210** can split and grow a decision tree to optimize the determined probability that the given entity is a member of a particular category. As another example, the training data **122** (FIG. **1**) can be used to prune the decision tree, such as to avoid overfitting.

[0034] In some implementations, a feature such as "Classification and Regression Trees" (CART) can be used. In such implementations, the spend-weighted rule component **210** can include or be based on a CART classifier. For example, CART models can be constructed with a customized pruning procedure (e.g., a stopping rule). As another example, error estimations of the CART model can be calculated using 10-fold cross validation.

[0035] In some implementations, the rule set **212** includes a classification decision tree of one-dimensional rules for mapping a set of (e.g., three) revenue weighted verticals into one

vertical for the entity. For example, this can provide the benefit of greater generalization capability in the system **200**, such as to allow pruning of "bad verticals" and/or other systemic errors from the base classifier **206**.

[0036] In generating the rule set **212**, financial data can be taken into account. In some implementations, data can be replicated when a CART model is constructed, such as to proportionate the amount of replication with the spent amount(s). For example, data corresponding to a relatively high total and/or quarterly spend level can be oversampled. As another example, data corresponding to a relatively low total and/or quarterly spend level can be undersampled. In some implementations, additional training data points based on revenue can tend to bias the final output (e.g., the selection of one or more categories) to high-spending entities (e.g., content providers) and improve accuracy regarding these entities.

[0037] An example of the rule set **212**, here a decision tree, is presented below in Appendix I.

[0038] The system **100** can include a primary vertical classifier **214**. In some implementations, the classifier can statically map a set of revenue-weighted categories (e.g., the weighted verticals **208**) into a single primary vertical for the entity. For example, the classifier **214** can use the rule set **212** (such as by loading a CART classification tree generated by the component **210**) to select one of the weighted categories from the base classifier **206**.

[0039] FIG. **3** shows an example user interface **300** that can present information based on a category having been identified for an entity. In some implementations, the front end component **124** (FIG. **1**) can generate the user interface **300**, such as to an actor in the system **100**. In some implementations, the user interface **300** can be used to manage customer relationships, such as to monitor and/or track participants in a content distribution program, such as an advertising campaign. The user interface **300** can include a "name" area **302** where an identifier for one or more entities can be presented, such as the name of an advertiser and/or another content provider. The user interface **300** can include a "vertical" area **304** where a category identified for the entity can be indicated, such as a vertical from the catalog **116**. The user interface **300** can include one or more areas presenting information relating to the category assigned to the entity, such as a "seasonality" area **306**. For example, companies engaged in a particular vertical (e.g., tax preparation consultants or flower retailers) can have seasonally occurring fluctuations in their business and/or other activities. In some implementations, such a seasonality (e.g., an information that "this entity's business might peak around Valentine's Day") can be output to a user. In some implementations, the related information (e.g., the seasonality area **306**) can be output without explicitly indicating the selected vertical. The user interface **300** can include a "search" control **308** by which the user can search for entities using one or more criteria, and results of such searches can be presented by populating information in one or more of the areas **302-306**. The user interface **300** can include a "contact" control **310** by which the user can initiate a contact with one or more entities, such as by email or telephone. For example, upon seeing information in the seasonality area **306**, a user such as a sales representative might contact the entity to make sure its needs are met regarding the busy season.

[0040] FIG. **4** shows an example method **400** that can be performed to identify a category for an entity. The method **400** can be performed by a processor executing instructions stored in a computer-readable medium, for example in the systems **100** and/or **200**. In some implementations, one or more of the steps can be performed in another order; as another example, more or fewer steps can be performed.

[0041] Step **410** includes determining a probability value for each of at least a subset of a plurality of categories. The probability value can represent a likelihood that an identified entity belongs to the respective category and can be determined using information about the entity. For example, the probability classifier **112** and/or the base classifier can generate the weighted verticals **208** for a particular entity such as a content provider or a content publisher. The subset can include one or more categories.

[0042] Step **420** includes recording one of the plurality of categories for the entity, the category identified using the probability value and a rule set for the plurality of categories that is based on, for example, training data. For example, the rule based classifier **114** and/or the primary vertical classifier **214** can select one vertical from the catalog **116** to be associated with the particular entity.

[0043] Step **430** includes presenting information based on the identification of a category for the entity. For example, the front end component **124** can generate the user interface **300** that can present the seasonality area **306**

[0044] FIG. **5** is a schematic diagram of a generic computer system **500**. The system **500** can be used for the operations described in association with any of the computer-implement methods described previously, according to one implementation. The system **500** includes a processor **510**, a memory **520**, a storage device **530**, and an input/output device **540**. Each of the components **510**, **520**, **530**, and **540** are interconnected using a system bus **550**. The processor **510** is capable of processing instructions for execution within the system **500**. In one implementation, the processor **510** is a single-threaded processor. In another implementation, the processor **510** is a multi-threaded processor. The processor **510** is capable of processing instructions stored in the memory **520** or on the storage device **530** to display graphical information for a user interface on the input/output device **540**.

[0045] The memory **520** stores information within the system **500**. In one implementation, the memory **520** is a computer-readable medium. In one implementation, the memory **520** is a volatile memory unit. In another implementation, the memory **520** is a non-volatile memory unit.

[0046] The storage device **530** is capable of providing mass storage for the system **500**. In one implementation, the storage device **530** is a computer-readable medium. In various different implementations, the storage device **530** may be a floppy disk device, a hard disk device, an optical disk device, or a tape device.

[0047] The input/output device **540** provides input/output operations for the system **500**. In one implementation, the input/output device **540** includes a keyboard and/or pointing device. In another implementation, the input/output device **540** includes a display unit for displaying graphical user interfaces.

[0048] The features described can be implemented in digital electronic circuitry, or in computer hardware, firmware, software, or in combinations of them. The apparatus can be implemented in a computer program product tangibly embodied in an information carrier, e.g., in a machine-readable storage device or in a propagated signal, for execution by a programmable processor; and method steps can be per-

formed by a programmable processor executing a program of instructions to perform functions of the described implementations by operating on input data and generating output. The described features can be implemented advantageously in one or more computer programs that are executable on a programmable system including at least one programmable processor coupled to receive data and instructions from, and to transmit data and instructions to, a data storage system, at least one input device, and at least one output device. A computer program is a set of instructions that can be used, directly or indirectly, in a computer to perform a certain activity or bring about a certain result. A computer program can be written in any form of programming language, including compiled or interpreted languages, and it can be deployed in any form, including as a stand-alone program or as a module, component, subroutine, or other unit suitable for use in a computing environment.

[0049] Suitable processors for the execution of a program of instructions include, by way of example, both general and special purpose microprocessors, and the sole processor or one of multiple processors of any kind of computer. Generally, a processor will receive instructions and data from a read-only memory or a random access memory or both. The essential elements of a computer are a processor for executing instructions and one or more memories for storing instructions and data. Generally, a computer will also include, or be operatively coupled to communicate with, one or more mass storage devices for storing data files; such devices include magnetic disks, such as internal hard disks and removable disks; magneto-optical disks; and optical disks. Storage devices suitable for tangibly embodying computer program instructions and data include all forms of non-volatile memory, including by way of example semiconductor memory devices, such as EPROM, EEPROM, and flash memory devices; magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and CD-ROM and DVD-ROM disks. The processor and the memory can be supplemented by, or incorporated in, ASICs (application-specific integrated circuits).

[0050] To provide for interaction with a user, the features can be implemented on a computer having a display device such as a CRT (cathode ray tube) or LCD (liquid crystal display) monitor for displaying information to the user and a keyboard and a pointing device such as a mouse or a trackball by which the user can provide input to the computer.

[0051] The features can be implemented in a computer system that includes a back-end component, such as a data server, or that includes a middleware component, such as an application server or an Internet server, or that includes a front-end component, such as a client computer having a graphical user interface or an Internet browser, or any combination of them. The components of the system can be connected by any form or medium of digital data communication such as a communication network. Examples of communication networks include, e.g., a LAN, a WAN, and the computers and networks forming the Internet.

[0052] The computer system can include clients and servers. A client and server are generally remote from each other and typically interact through a network, such as the described one. The relationship of client and server arises by virtue of computer programs running on the respective computers and having a client-server relationship to each other.

[0053] A number of embodiments have been described. Nevertheless, it will be understood that various modifications may be made without departing from the spirit and scope of this disclosure. Accordingly, other embodiments are within the scope of the following claims.

Appendix I

CART Model Description and Output

Independent Variables

[0054] x1: Country(e.g., by country code)
[0055] x2: Keyword Count
[0056] x3: Total Spend (USD)
[0057] x4: Quarterly Spend (USD)
[0058] x5~x34: Revenue weights for verticals ordered from smallest to largest (e.g., the output of the classifier **112** or **206**)

	Id									
	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14
Vertical	2	3	4	5	7	8	11	12	13	14
	x15	x16	x17	x18	x19	x20	x21	x22	x23	x24
Vertical	15	16	18	19	20	29	44	45	47	52
	x25	x26	x27	x28	x29	x30	x31	x32	x33	x34
Vertical	66	67	71	174	285	299	397	439	533	570

CART Output

Decision Tree for Classification

[0059] 1 if x26<0.156561 then node 2 else node 3
[0060] 2 if x9<0.370092 then node 4 else node 5
[0061] 3 if x26<0.657022 then node 6 else node 7
[0062] 4 if x17<0.495845 then node 8 else node 9
[0063] 5 if x9<0.823663 then node 10 else node 11
[0064] 6 if x15<0.0685697 then node 12 else node 13
[0065] 7 if x21<0.0848807 then node 14 else node 15

[0066] 8 if x8<0.521697 then node 16 else node 17

[0067] 9 if x17<0.736217 then node 18 else node 19

[0068] 10 if x23<0.498586 then node 20 else node 21

[0069] 11 class=7

[0070] 12 if x20<0.257736 then node 22 else node 23

[0071] 13 if x20<00258419 then node 24 else node 25

[0072] 14 class=67

[0073] 15 if x2<7168.5 then node 26 else node 27

[0074] 16 if x24<0.354713 then node 28 else node 29

[0075] 17 if x8<0.716763 then node 30 else node 31

[0076] 18 if x2<80663 then node 32 else node 33

[0077] 19 if x17<0.925121 then node 34 else node 35

[0078] 20 if x18<0.213272 then node 36 else node 37

[0079] 21 class=47

[0080] 22 if x12<0.335248 then node 38 else node 39

[0081] 23 if x1 in {1 3 4 6} then node 40 else node 41

[0082] 24 if x29<0.230442 then node 42 else node 43

[0083] 25 class=29

[0084] 26 class=44

[0085] 27 class=52

[0086] 28 if x1 1<0.331887 then node 44 else node 45

[0087] 29 class=52

[0088] 30 if x2<7057.5 then node 46 else node 47

[0089] 31 class=5

[0090] 32 if x7<0.0829784 then node 48 else node 49

[0091] 33 if x1=1 then node 50 else node 51

[0092] 34 if x2<77348 then node 52 else node 53

[0093] 35 class=18

[0094] 36 if x20<0.371657 then node 54 else node 55

[0095] 37 if x3<3.85033e+06 then node 56 else node 57

[0096] 38 if x19<0.330368 then node 58 else node 59

[0097] 39 class=12

[0098] 40 class=29

[0099] 41 class=67

[0100] 42 class=67

[0101] 43 class=285

[0102] 44 if x23<0.57222 then node 60 else node 61

[0103] 45 if x7<0.114347 then node 62 else node 63

[0104] 46 if x13<0.330393 then node 64 else node 65

[0105] 47 if x7<0.255785 then node 66 else node 67

[0106] 48 if x1 in {1 2 3 7 8 10} then node 68 else node 69

[0107] 49 class=4

[0108] 50 class=11

[0109] 51 class=285

[0110] 52 class=18

[0111] 53 class=20

[0112] 54 class=7

[0113] 55 class=29

[0114] 56 class=7

[0115] 57 class=19

[0116] 58 if x21<0.203319 then node 70 else node 71

[0117] 59 class=20

[0118] 60 if x3<4.08266e+07 then node 72 else node 73

[0119] 61 if x23<0.730036 then node 74 else node 75

[0120] 62 if x 1<0.537014 then node 76 else node 77

[0121] 63 if x1 in {1 2 8 10} then node 78 else node 79

[0122] 64 if x24<0.10869 then node 80 else node 81

[0123] 65 if x2<1310 then node 82 else node 83

[0124] 66 if x1 in {1 2 5 7} then node 84 else node 85

[0125] 67 class=4

[0126] 68 class=18

[0127] 69 if x2<39894 then node 86 else node 87

[0128] 70 if x13<0.193039 then node 88 else node 89

[0129] 71 class=44

[0130] 72 if x22<0.442255 then node 90 else node 91

[0131] 73 class=5

[0132] 74 if x12<0. 179846 then node 92 else node 93

[0133] 75 class=47

[0134] 76 if x27<0. 189842 then node 94 else node 95

[0135] 77 class=11

[0136] 78 class=4

[0137] 79 class=11

[0138] 80 class=5

[0139] 81 if x1 in {1 3 6 8 10} then node 96 else node 97

[0140] 82 class=13

[0141] 83 class=5

[0142] 84 if x32<0.117921 then node 98 else node 99

[0143] 85 class=5

[0144] 86 if x21<0.268462 then node 100 else node 101

[0145] 87 class=52

[0146] 88 if x17<0.209712 then node 102 else node 103

[0147] 89 class=13

[0148] 90 if x7<0.35475 then node 104 else node 105

[0149] 91 if x22<0.711517 then node 106 else node 107

[0150] 92 if x2<10.5 then node 108 else node 109

[0151] 93 class=12

[0152] 94 if x4<368742 then node 110 else node 111

[0153] 95 class=71

[0154] 96 class=5

[0155] 97 class=52

[0156] 98 class=19

[0157] 99 class=18

[0158] 100 class=18

[0159] 101 class=44

[0160] 102 if x23<0.262412 then node 112 else node 113

[0161] 103 class=18

[0162] 104 if x18<0.513483 then node 114 else node 115

[0163] 105 class=4

[0164] 106 if x21<0.210351 then node 116 else node 117

[0165] 107 class=45

[0166] 108 class=18

[0167] 109 class=47

[0168] 110 if x12<0.433287 then node 118 else node 119

[0169] 111 class=11

[0170] 112 if x7<0.569093 then node 120 else node 121

[0171] 113 class=47

[0172] 114 if x20<0.473106 then node 122 else node 123

[0173] 115 if x22<0.158422 then node 124 else node 125

[0174] 116 if x6<0.0777122 then node 126 else node 127

[0175] 117 if x21<0.470751 then node 128 else node 129

[0176] 118 if x3<1.47723e+06 then node 130 else node 131

[0177] 119 if x3<5.20398e+06 then node 132 else node 133

[0178] 120 if x14<0.396659 then node 134 else node 135

[0179] 121 class=4

[0180] 122 if x12<0.470398 then node 136 else node 137

[0181] 123 if x17<0.306859 then node 138 else node 139

[0182] 124 if x18<0.824979 then node 140 else node 141

[0183] 125 class=19

[0184] 126 class=45

[0185] 127 if x3<1.93593e+06 then node 142 else node 143

[0186] 128 if x3<1.44848e+06 then node 144 else node 145

[0187] 129 class=45

[0188] 130 class=11

[0189] 131 class=8

[0190] 132 if x1 in {1 4 5 6 8} then node 146 else node 147

[0191] 133 class=11

[0192] 134 if x 1<0.09162 then node 148 else node 149

[0193] 135 class=14

[0194] 136 if x21<0.385516 then node 150 else node 151
[0195] 137 if x12<0.821368 then node 152 else node 153
[0196] 138 class=29
[0197] 139 class=18
[0198] 140 if x4<104730 then node 154 else node 155
[0199] 141 if x27<0.019163 then node 156 else node 157
[0200] 142 class=2
[0201] 143 class=29
[0202] 144 if x4<2953.45 then node 158 else node 159
[0203] 145 class=44
[0204] 146 class=12
[0205] 147 if x3<361231 then node 160 else node 161
[0206] 148 if x9<0.384375 then node 162 else node 163
[0207] 149 class=11
[0208] 150 if x14<0.452462 then node 164 else node 165
[0209] 151 class=44
[0210] 152 if x7<0.159118 then node 166 else node 167
[0211] 153 class=12
[0212] 154 if x3<1.58799e+06 then node 168 else node 169
[0213] 155 class=19
[0214] 156 class=19
[0215] 157 class=13
[0216] 158 class=44
[0217] 159 class=45
[0218] 160 if x2<653 then node 170 else node 171
[0219] 161 class=11
[0220] 162 if x24<0.262085 then node 172 else node 173
[0221] 163 class=7
[0222] 164 if x13<0.32757 then node 174 else node 175
[0223] 165 if x30<0.28577 then node 176 else node 177
[0224] 166 if x 18<0.247799 then node 178 else node 179
[0225] 167 class=4
[0226] 168 if x 13<0.00967496 then node 180 else node 181
[0227] 169 class=18
[0228] 170 class=11
[0229] 171 class=12
[0230] 172 if x8<0.281417 then node 182 else node 183
[0231] 173 class=52
[0232] 174 if x30<0.258444 then node 184 else node 185
[0233] 175 if x 13<0.779286 then node 186 else node 187
[0234] 176 class=14
[0235] 177 class=299
[0236] 178 if x11<0.0620939 then node 188 else node 189
[0237] 179 class=19
[0238] 180 if x19<0.123657 then node 190 else node 191
[0239] 181 class=13
[0240] 182 class=67
[0241] 183 class=5
[0242] 184 if x33<0.118834 then node 192 else node 193
[0243] 185 if x1 in {1 2 3 5 6 7 8} then node 194 else node 195
[0244] 186 if x33<0.326535 then node 196 else node 197
[0245] 187 class=13
[0246] 188 if x17<0.114527 then node 198 else node 199
[0247] 189 if x12<0.640493 then node 200 else node 201
[0248] 190 class=19
[0249] 191 class=20
[0250] 192 if x10<0.508978 then node 202 else node 203
[0251] 193 if x33<0.544036 then node 204 else node 205
[0252] 194 if x13<0.0837794 then node 206 else node 207
[0253] 195 if x30<0.620821 then node 208 else node 209
[0254] 196 if x32<0.085737 then node 210 else node 211
[0255] 197 class=533
[0256] 198 class=12
[0257] 199 if x4<34722.4 then node 212 else node 213
[0258] 200 class=11
[0259] 201 class=12
[0260] 202 if x32<0.33374 then node 214 else node 215
[0261] 203 class=8
[0262] 204 if x8<0.00714825 then node 216 else node 217
[0263] 205 class=533
[0264] 206 if x 15<0.248854 then node 218 else node 219
[0265] 207 if x3<709455 then node 220 else node 221
[0266] 208 class=2
[0267] 209 if x30<0.818431 then node 222 else node 223
[0268] 210 class=13
[0269] 211 class=439
[0270] 212 class=18
[0271] 213 class=12
[0272] 214 if x27<0.445613 then node 224 else node 225
[0273] 215 if x30<0.0232432 then node 226 else node 227
[0274] 216 class=533
[0275] 217 class=5
[0276] 218 class=299
[0277] 219 if x1 in {1 2 3 5 7 8} then node 228 else node 229
[0278] 220 class=299
[0279] 221 class=13
[0280] 222 class=299
[0281] 223 class=2
[0282] 224 if x19<0.0842646 then node 230 else node 231
[0283] 225 class=71
[0284] 226 class=439
[0285] 227 class=2
[0286] 228 class=299
[0287] 229 class=52
[0288] 230 if x15<0.792343 then node 232 else node 233
[0289] 231 if x3<1.43634e+06 then node 234 else node 235
[0290] 232 if x34<0.432739 then node 236 else node 237
[0291] 233 if x20<0.00676158 then node 238 else node 239
[0292] 234 if x4<142308 then node 240 else node 241
[0293] 235 if x3<2.28536e+06 then node 242 else node 243
[0294] 236 if x6<0.343384 then node 244 else node 245
[0295] 237 class=570
[0296] 238 if x26<2.31392e−13 then node 246 else node 247
[0297] 239 class=29
[0298] 240 class=20
[0299] 241 class=18
[0300] 242 if x4<177429 then node 248 else node 249
[0301] 243 class=7
[0302] 244 if x25<0.735451 then node 250 else node 251
[0303] 245 if x14<0.037943 then node 252 else node 253
[0304] 246 if x4<44870.6 then node 254 else node 255
[0305] 247 if x1 in {1 3 4 7 10} then node 256 else node 257
[0306] 248 class=47
[0307] 249 if x1=1 then node 258 else node 259
[0308] 250 if x29<0.376623 then node 260 else node 261
[0309] 251 class=66
[0310] 252 if x6<0.904535 then node 262 else node 263
[0311] 253 if x2<782 then node 264 else node 265
[0312] 254 if x17<0.0111276 then node 266 else node 267
[0313] 255 class=15
[0314] 256 class=67
[0315] 257 class=15
[0316] 258 class=45
[0317] 259 class=18
[0318] 260 if x9<0.127178 then node 268 else node 269

[0319] 261 if x29<0.720004 then node 270 else node 271
[0320] 262 if x8<0.0786027 then node 272 else node 273
[0321] 263 if x4<224146 then node 274 else node 275
[0322] 264 class=3
[0323] 265 class=2
[0324] 266 class=15
[0325] 267 class=2
[0326] 268 if x20<0.107796 then node 276 else node 277
[0327] 269 if x3<2.68169e+06 then node 278 else node 279
[0328] 270 if x14<0.0382579 then node 280 else node 281
[0329] 271 class=285
[0330] 272 if x30<00283009 then node 282 else node 283
[0331] 273 if x24<0.0668307 then node 284 else node 285
[0332] 274 if x19<0.0325977 then node 286 else node 287
[0333] 275 class=2
[0334] 276 if x16<0.487338 then node 288 else node 289
[0335] 277 if x15<0.486436 then node 290 else node 291
[0336] 278 if x9<0.366797 then node 292 else node 293
[0337] 279 class=13
[0338] 280 if x11<0.0434011 then node 294 else node 295
[0339] 281 class=14
[0340] 282 if x3<1.79108e+06 then node 296 else node 297
[0341] 283 class=2
[0342] 284 if x1 in {1 2 4 5 7} then node 298 else node 299
[0343] 285 class=52
[0344] 286 class=3
[0345] 287 class=52
[0346] 288 if x17<0.188053 then node 300 else node 301
[0347] 289 class=16
[0348] 290 if x23<0.249635 then node 302 else node 303
[0349] 291 class=29
[0350] 292 class=7
[0351] 293 class=45
[0352] 294 class=285
[0353] 295 class=11
[0354] 296 if x25<0.0849167 then node 304 else node 305
[0355] 297 if x6<0.816804 then node 306 else node 307
[0356] 298 class=5
[0357] 299 class=3
[0358] 300 if x3<5.75773e+06 then node 308 else node 309
[0359] 301 if x23<0.367225 then node 310 else node 311
[0360] 302 if x15<0.0297698 then node 312 else node 313
[0361] 303 if x1=4 then node 314 else node 315
[0362] 304 if x24<0.0109364 then node 316 else node 317
[0363] 305 class=66
[0364] 306 class=3
[0365] 307 class=2
[0366] 308 if x18<0.358197 then node 318 else node 319
[0367] 309 class=45
[0368] 310 if x14<0.30828 then node 320 else node 321
[0369] 311 if x1 in {1 2 4 10} then node 322 else node 323
[0370] 312 class=4
[0371] 313 if x1 in {1 2 3 4 6 8} then node 324 else node 325
[0372] 314 class=47
[0373] 315 class=15
[0374] 316 if x7<0.0529852 then node 326 else node 327
[0375] 317 class=52
[0376] 318 if x8<0.250055 then node 328 else node 329
[0377] 319 class=19
[0378] 320 if x34<0.299071 then node 330 else node 331
[0379] 321 class=14
[0380] 322 class=47
[0381] 323 class=14
[0382] 324 if x1 in {1 8} then node 332 else node 333
[0383] 325 class=533
[0384] 326 if x18<0.346103 then node 334 else node 335
[0385] 327 class=4
[0386] 328 if x12<0.00523925 then node 336 else node 337
[0387] 329 if x3<1.54296e+06 then node 338 else node 339
[0388] 330 class=18
[0389] 331 class=570
[0390] 332 class=29
[0391] 333 class=19
[0392] 334 if x34<0.24078 then node 340 else node 341
[0393] 335 class=19
[0394] 336 if x24<0.0618855 then node 342 else node 343
[0395] 337 if x7<0.269018 then node 344 else node 345
[0396] 338 if x1 in {1 5 6 10} then node 346 else node 347
[0397] 339 class=18
[0398] 340 if x6<0.744853 then node 348 else node 349
[0399] 341 class=570
[0400] 342 if x25<0.725171 then node 350 else node 351
[0401] 343 class=52
[0402] 344 if x11<0.145951 then node 352 else node 353
[0403] 345 class=4
[0404] 346 class=5
[0405] 347 if x7<0.074593 then node 354 else node 355
[0406] 348 if x1 in {1 2 3 7 8 9 10} then node 356 else node 357
[0407] 349 class=3
[0408] 350 if x3<312875 then node 358 else node 359
[0409] 351 class=7
[0410] 352 if x4<40808.4 then node 360 else node 361
[0411] 353 class=11
[0412] 354 if x1 in {23 4 8} then node 362 else node 363
[0413] 355 class=4
[0414] 356 if x3<602261 then node 364 else node 365
[0415] 357 class=16
[0416] 358 if x28<0.99751 then node 366 else node 367
[0417] 359 if x10<0.204898 then node 368 else node 369
[0418] 360 class=12
[0419] 361 class=15
[0420] 362 if x3<579398 then node 370 else node 371
[0421] 363 class=13
[0422] 364 if x1 in {1 2 3 8 9} then node 372 else node 373
[0423] 365 class=533
[0424] 366 if x25<0.389004 then node 374 else node 375
[0425] 367 class=174
[0426] 368 class=15
[0427] 369 class=8
[0428] 370 if x2<95 then node 376 else node 377
[0429] 371 class=67
[0430] 372 if x3<56290.8 then node 378 else node 379
[0431] 373 class=2
[0432] 374 if x21<0.073466 then node 380 else node 381
[0433] 375 class=66
[0434] 376 class=12
[0435] 377 class=5
[0436] 378 class=3
[0437] 379 class=18
[0438] 380 if x15<0.329107 then node 382 else node 383
[0439] 381 class=44
[0440] 382 class=14
[0441] 383 class=15

What is claimed is:

1. A computer-implemented method for associating an entity with a category, the method comprising:

determining a probability value for each of at least a subset of a plurality of categories, the probability value representing a likelihood that an identified entity belongs to the respective category and determined using information about the entity; and

recording one of the plurality of categories for the entity, the category identified using the probability value and a rule set for the plurality of categories.

2. The computer-implemented method of claim 1, wherein the entity is a content provider identified as enrolled in a program in which the content provider provides content to be published by at least one publisher, and wherein the probability value is determined using at least one keyword associated with the content provider and at least one financial value associated with the content provider.

3. The computer-implemented method of claim 2, wherein determining the probability value comprises:

mapping the at least one keyword at least to the subset of the plurality of categories;

weighting at least the subset with the at least one financial value, wherein the financial value has been assigned to the corresponding keyword; and

selecting a predetermined number of the categories as the subset.

4. The computer-implemented method of claim 1, wherein the rule set is based on training data.

5. The computer-implemented method of claim 4, wherein the rule set includes a decision tree configured for selecting one of the plurality of categories by processing at least some of a plurality of decisions included in the decision tree.

6. The computer-implemented method of claim 5, further comprising:

generating the decision tree using the training data, wherein the training data comprises mappings of entities to one or more of the plurality of categories.

7. The computer-implemented method of claim 6, wherein generating the decision tree further comprises:

weighting the mappings using financial data regarding the entities.

8. The computer-implemented method of claim 7, wherein weighting the mappings further comprises:

oversampling at least a subset of the mappings based on the financial data corresponding to the subset of the mappings.

9. The computer-implemented method of claim 5, wherein generating the decision tree comprises:

selecting a structure for the decision tree;

determining an extent of the decision tree, including how many of the plurality of decisions to be made before the one of the plurality of categories is selected; and

determining threshold values to be used in the plurality of decisions.

10. The computer-implemented method of claim 8, wherein the decision tree is generated iteratively.

11. The computer-implemented method of claim 6, wherein the content provider is engaged in advertising and wherein the plurality of categories include verticals with which the content provider is to be matched.

12. The computer-implemented method of claim 10, wherein generating the decision tree further comprises:

identifying at least one of the verticals for which the determination of the probability values has a tendency to improperly assign the vertical to the content provider; and

selecting at least one of the threshold values so that the tendency is reduced.

13. The computer-implemented method of claim 1, further comprising:

presenting information to a user based on the category having been identified for the entity.

14. The computer-implemented method of claim 12, wherein the information indicates a seasonality associated with the category.

15. A computer system comprising:

a first classifier determining a probability value for each category of at least a subset of a plurality of categories, the probability value representing a likelihood that an identified entity belongs to the respective category and determined using information about the entity; and

a second classifier identifying one of the plurality of categories for the entity using the probability value and a rule set for the plurality of categories.

16. The computer system of claim 14, wherein the rule set is based on training data.

17. The computer system of claim 16, wherein the rule set includes a decision tree configured for selecting one of the plurality of categories by processing at least some of a plurality of decisions included in the decision tree, the computer system further comprising:

a rule component generating the decision tree using the training data, wherein the training data comprises mappings of entities to one or more of the plurality of categories.

18. The computer system of claim 17, wherein the rule component weights the mappings using financial data regarding the entities, including oversampling at least a subset of the mappings based on the financial data corresponding to the subset of the mappings.

19. The computer system of claim 14, further comprising:

a front end component presenting information to a user based on the second classifier having identified the category for the entity.

20. A computer-implemented method for associating a content provider with a category, the method comprising:

identifying a content provider as enrolled in a program in which the content provider provides content to be published by at least one publisher;

receiving at least one keyword regarding the content provider and at least one financial value regarding the keyword;

receiving a plurality of categories, wherein the content provider is to be associated with at least one of the categories;

mapping the at least one keyword to a subset of the categories based on names of the categories;

associating each of at least the subset of the categories with a probability value representing a likelihood that the

content provider should be associated with the respective category, the probability values weighted using the financial value;

receiving a rule set generated regarding the plurality of categories, the rule set configured for use in identifying one of the categories;

processing data regarding the content provider using the rule set, the data including at least: (i) the probability value for each of at least the subset of the categories (ii) financial data regarding the content provider; (iii) a geographic region with which the content provider is associated;

selecting one of the plurality of categories for the content provider based on the processing of the data; and

associating the content provider with the selected category.

* * * * *